J. Int. Financ. Markets Inst. Money 96 (2024) 102042

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Fall of dwarfs: micro and macroeconomic determinants of the disappearance of European small banks

Federica Poli[a,*,1], Simone Rossi[b], Mariarosa Borroni[a]

[a] Department of Economic Sciences and Business Administration, Università Cattolica del Sacro Cuore, Milan, Italy
[b] Department of Economic and Social Sciences, Università Cattolica del Sacro Cuore, Piacenza, Italy

ARTICLE INFO

JEL codes:
G21
G28
G17

ABSTRACT

Based on a wide sample of banks headquartered in 27 European countries over the period 2005–2022, this paper tests the influence that microeconomic and macroeconomic variables have on the probability of small banks exiting the market, evaluating the predictive power of the explanatory models employed. Our approach to the determinants of small banks' exit proves that even the macroeconomic and socio-demographic reference context can have a predictive effectiveness similar to that of the accounting variables, especially when contagion effects at the local level are taken into account.

1. Introduction and literature review

After the outbreak of the global financial crisis that followed the collapse of Lehman Brothers, the major world economies witnessed a significant increase in regulatory and supervisory activities. The purpose of this action was mainly to contain and prevent the distress of systemically important subjects (so-called too-big-to-fail banks), and the potentially related phenomena of transmission of financial instability at a global level. Within the European Union, alongside the strengthening of banks' capital requirements determined by the introduction of the Basel III agreements, the ambitious project of the Banking Union codified new rules for the supervision and crisis management of so-called significant entities. Overall, attention was therefore mainly directed towards intermediaries deemed too big to fail, neglecting (or, from a less radical viewpoint, paying less attention to) small and medium-sized banks. For these, the supervision and crisis management safeguards that were already in force have been maintained, with a significant degree of national discretion. This asymmetric treatment was the natural outcome of the regulators' view, which judged smaller independent banks to be entities incapable of generating systemic impacts in the event of a crisis; an assumption which has proved to be incorrect (Enria 2021). In fact, failures of small banks in the United States and Europe have shown that the distress of these banks can generate negative spillovers which exceed the expectations of the regulators. However, even in the empirical literature, the effort dedicated to investigating small banking entities appears very slight and is often focused on the US market, where community banks play an important role, especially in rural areas, and have been less impacted by the consolidation process that has taken place over the last decade (Federal Deposit Insurance Corporation 2020).

In many European countries, small-sized banks still represent a very significant share of the banking institutions: less significant

* Corresponding author at: Department of Economic Sciences and Business Administration, Università Cattolica del Sacro Cuore, Largo Gemelli 1, 20123 Milano, Italy.

E-mail address: federica.poli@unicatt.it (F. Poli).

[1] Orcid: 0000-0002-1660-4971.

https://doi.org/10.1016/j.intfin.2024.102042
Received 29 November 2023; Accepted 4 August 2024
Available online 8 August 2024

institutions (LSIs) accounted for approximately 95 % of the total banks at the end of 2021 (European Central Bank 2022). At the same date, the banks included in our dataset (which hold total assets not exceeding 5 billion euros thus being a subsample of LSIs) account for 49.8 % of the total number and 8.9 % of the total assets of all credit institutions in EU27 countries (our elaborations on Bankscope/BankFocus, European Central Bank and European Banking Federation data).

Despite a widespread consolidation process having taken place in the banking sector, small-sized banks continue to exist and, if well managed, where their market share is noteworthy, they also significantly reduce the likelihood of episodes of economic recession occurring in their area (Chiorazzo et al. 2018), as well as the duration of such episodes (Petach et al. 2021; Scott Langford and Feldman 2022), contrary to what has been found for large banks (Calice and Gam 2023). The geographical concentration of small banks' operations may expose them to the risk of local economic downturns, but situations of this kind are not systematically reflected in their performance (Yeager 2004). In essence: "small is not necessarily ugly", i.e., synonymous with greater risks and negative performance in the long run. Considerations of this kind are also shared by Barth et al. (2023) who analyze small US minority banks over a time horizon of almost twenty years and verify that their degree of risk and their level of profitability are similar to that of other banks. Berger and Bouwman (2013) also obtain analogous findings: high capital endowment, stable funding, a good level of profitability, and higher insulation from downturns in capital markets are always trump cards for small banks, but even more so in times of crisis. Although their business model is quite traditional (the collection of deposits and financing of small and medium-sized local businesses), the emphasis placed on personalizing the service they provide and the extensive use of soft information in their customer relationships endows them with a competitive advantage vis-à-vis large banks (DeYoung et al. 2004), even in difficult periods such as the months characterized by the COVID-19 pandemic (Li and Strahan 2021).

Small banks remain a safeguard that allows the benefits of relationship banking to unfold; they play an active role in supporting the territory in which they are located, they promote values of mutuality and stakeholder focus (e.g., cooperative banks), and ultimately reduce the risk of financial exclusion and the development of "banking deserts". This explains, for instance, the numerous studies on small business lending and the contribution this makes to local and nationwide economic growth, especially in those countries characterized by the widespread presence of small banks and an economic environment in which SMEs play a key role (e.g., on the Italian case, see Bellucci et al. 2013; Coccorese and Shaffer 2021).

On the other hand, the literature that investigates small banks *per se* and, in particular, their ability to survive within the local environment is limited: where available, the analyses in question above all examine individual countries or limited geographical areas in which there is a high number of small banks, often following a specific business model, such as e.g. cooperative banking (Halling and Hayden 2008; Fiordelisi and Mare 2013; Chernykh 2014; Mare 2015). One contribution of this study is therefore to overcome these limitations by investigating the determinants of the disappearance of small banks in a supranational context, such as the European Union.

In the existing empirical literature that has investigated the determinants of bank failure or the disappearance of banks due to mergers and acquisitions (Worthington 2004; Beccalli and Frantz 2013), both micro and/or macroeconomic variables are introduced. The former are seen as capable of capturing the fundamental sources of ex-ante risk (Gonzalez-Hermosillo 1999; Maggiolini and Mistrulli 2005; Mare 2015) while the latter variables may improve the predictive power of the models based on bank-specific data only (Arena 2008; Männasoo and Mayes 2009; Ioannidis et al. 2010; Betz et al. 2014; Mare 2015). In fact, given the restricted operations of small banks, both in terms of financial activity and geographical reach, their sensitivity to the state of the local economy may prove to be high. A novel element of our research is that we enrich the set of macroeconomic variables with indicators that reflect at a socio-demographic level the human capital that exists in the regions in which small banks operate. The limited research available on the survival of small banks at the country level (e.g., Ostergaard et al. 2016 for Norway) shows that the quality of local human capital (or the lack thereof) strengthens/weakens the resilience of small banks.

Additionally, based on the work of Hardy (1998) and more recently, Poghosyan and Čihak (2011), we also run separate estimations to test the relative importance of other potential sources of bank exit, such as contagion effects between small banks located in limited geographical areas. It is worth noting that at the regional level, the failure of small banks may more easily create rumors and, potentially, bank-run phenomena. As far as we know, this is the first research to examine the effects of contagion among small banks, and specifically at a European level.

Motivated by these research outcomes, we therefore aim to test, first separately and then jointly, the influence that typically-employed micro and macroeconomic variables, socio-demographic factors and contagion effects have on the probability of disappearance of small banks headquartered in 27 European countries over the period 2005–2022 and to evaluate the predictive power of such models. We use a discrete-time representation of a continuous time proportional hazards model, the complementary log–log model (cloglog), which is frequently used when the probability of an event is either very small or very large and survival occurs in continuous time, but spell length is observed only at intervals, as is the case for bank exits recorded on an annual basis in our sample (Männasoo and Mayes 2009; Mare 2015).

Our research contributes in several ways to the rather sparse literature on the determinants of the disappearance of small European banks. In the first instance, it confirms the role of size, capitalization, riskiness, and operational efficiency, in keeping with what has been found in other studies that are less territorially and longitudinally broad. Our approach to the determinants of small banks' disappearance proves that, for these banks, the macroeconomic and socio-demographic reference context can have a predictive effectiveness similar to that of the accounting variables, especially when contagion effects at a local level are taken into account.

Our study is one of the very few works to have considered the contagion effect at the local level, tested it, and identified its significance in explaining small banks' exit from the market (later in the text the terms 'disappearance' and 'exit' will be used interchangeably). Our evidence also demonstrates that the socio-demographic context in which dwarf banks operate deserves to be taken into due consideration given the strength of the relationship that exists between these intermediaries and their clients (Ostergaard et al.

2016).

Further, we account for the role played by monetary policy in explaining the pattern of small bank disappearance, contributing to the scientific debate and empirical evidence linked to the recent period of low or even negative rates.

The paper is organized as follows: section 2 introduces the sample and the methodology employed to analyze the available dataset; section 3 shows and discusses our results and includes several robustness checks; finally, section 4 presents policy implications and section 5 concludes.

2. Methodology, variables, and descriptive statistics

2.1. Empirical methodology and identification of target variables

To investigate the role of micro and macro determinants of the exit of small European banks (i.e. with total assets not exceeding 5 billion euros: more details are provided in section 2.3) over the period 2005–2022, we collected two sets of data, respectively reflecting accounting-based bank-specific information from annual financial statements provided by BankScope and BankFocus, and macroeconomic and socio-demographic information from Eurostat, the International Monetary Fund, and the European Central Bank. The macroeconomic and sociodemographic explanatory variables are collected both at the regional level (NUTS 2 level) and at the national level, where regional data is unavailable or where national data can be validly used in place of regional data. According to Eurostat, the NUTS classification (acronym of "Nomenclature of Territorial Units for Statistics") is a system which allows us to divide the territory of the European Union to collect statistics, analyze the socio-economic conditions of the different regions and frame regional policies. NUTS 2 level includes regions with an average minimum and maximum population threshold of respectively 800,000 and 3,000,000.

The preference for using macroeconomic and sociodemographic data at the regional level responds to the specific need to gain a better understanding of the conditions of the economic and social contexts in which small banks operate, given their limited ability to exploit the effects of geographical diversification.

The variables used in this empirical study were selected based on the literature that has so far investigated both the determinants of banks' disappearance, and the channels through which the survival of banks can be put at risk (for example at the bank balance sheet level and/or concerning the macroeconomic context of reference). Our analysis focuses on the near-term vulnerability of banks, identifying and evaluating potential idiosyncratic influence factors as well as regional and national structural weaknesses that can affect bank exits and incentives to screen and monitor risks.

In the empirical literature to date, different estimation approaches have been used to identify the determinants of bank exit from the market due to failure, distress, and/or acquisitions. For instance, Cleary and Hebb (2016) use multivariate discriminant analysis (MDA) to examine the failures of 132 U.S. banks over the 2002–2009 period. Wheelock and Wilson (2000) analyze the determinants of individual bank failures and acquisitions in the United States from 1984 to 1993 and use Cox (1972) proportional hazards (PH) models with time-varying covariates. Similarly, Cox et al. (2017) employ a set of Cox PH models to ascertain those financial ratios that distinguish US bank failures from 2005 to 2010; the same approach is used by Pappas et al. (2017) for a sample of 421 banks in 20 Middle and Far Eastern countries from 1995 to 2010. The fundamental assumption in the Cox model is that the hazards are proportional, which means that the relative hazard remains constant over time with different predictor or covariate levels. Additionally, the baseline hazard is an unspecified function, which makes it a semi-parametric model.

Logit and probit estimation models are also employed to analyze the determinants of bank exit. Estrella et al. (2000) estimate the likelihood of failure using cross-sectional logit regression on a sample of U.S. banks during the 1988–93 period to examine the relationship between bank failure and regulatory and non-regulatory capital ratios. Poghosyan and Čihak (2011) use a logistic probability model for a sample of European banks in the EU-25 countries from 1996–2007. Betz et al. (2014) focus on large EU banks which may hinder systemic stability from 2000 to 2013; they apply a logit model approach, analogously to other authors such as Cole and White (2012), Lo Duca and Peltonen (2013), and Sarlin and Peltonen (2013). Within the empirical literature, pooled logit models prevail over panel-based ones due to the relatively small number of bank crises at the country level (Betz et al. 2014). More recently, Chiorazzo et al. (2018) employ a pooled probit approach with time-fixed effects on a sample of small US commercial banks from 1997 to 2012. They argue that probit and logit models with firm-fixed effects do not produce consistent parameter estimates, and that those with random effects impose a distribution on the unobservable firm effects and require them to be independent of the other regressors (Wooldridge 2010).

Both logit and probit apply a symmetric link function to a linear combination of covariates. These symmetric link functions are found to have some limitations when the probability of the binomial response approaches 0 and 1 at different rates (as a function of covariate) (Chen et al. 1999). Asymmetric (or skewed) links may be more appropriate than a symmetric link function in unbalanced data (Czado and Santner 1992; Chen et al. 1999). The complementary log–log model (cloglog) is an asymmetric link function that can be used for a discrete-time representation of continuous time proportional hazards. The complementary log–log model specification for the hazard regression is consistent with a continuous time model and interval-censored survival time data (Jenkins 2005). The cloglog belongs to the discrete-time functional specifications applied when survival occurs in continuous time, but spell length is observed only at intervals as in our study, where bank exits are recorded annually. Guo (1993) observes that time-varying covariates offer an opportunity to examine the relationship between the probability of failure (or exit) and the changing conditions under which the exit happens. Equivalence between interval-censored discrete-time and continuous-time models with the proportional hazards assumption is shown by Prentice and Gloeckler (1978). Therefore, it is possible to transform the coefficients of this analysis into hazard ratios. The cloglog model yields estimates of the impact of the indicators on the conditional probability of bank disappearance, which means that we obtain probabilities of bank exit, conditional on surviving to a certain point in time. Each regression coefficient summarizes the effect on the hazard of absolute changes in the corresponding covariates with coefficients not varying with survival time.

Männasoo and Mayes (2009) use a discrete complementary log–log (cloglog) model as an estimation approach of banks' distress for a sample of nearly 600 banks in Eastern European transition countries over the years 1995–2004. The same method is used by Fiordelisi and Mare (2013), Chiaramonte et al. (2015), and Mare (2015) respectively on a sample of Italian cooperative banks during 1997 and 2009, of European banks from 12 countries over the period 2001–2011, and of Italian cooperative banks between 1993 and 2011. Based on these findings, we employ a cloglog model for our sample of small European banks from 2005 to 2022.

The cloglog with time-varying covariates assumes the following general form:

$$\Pr\left(y_j = 1|X\right) = 1 - \exp\left\{-\exp(\beta' X + \gamma_j)\right\}$$

where Pr is the probability that a bank exits the market in a given time interval j, X is the vector of the time-varying explanatory variables, lagged by one year, and γ_j summarizes differences in values of the integrated hazard function, and can be specified either by temporal dummy variables or by different parametric functional forms (Jenkins 2005).To deal with problems of time dependency that arise when using these models, we include the vector of temporal dummy variables for each spell year at risk of exit (Jenkins 2005; Chiaramonte et al. 2015). Additionally, we use robust standard errors clustered on the unit of analysis. The target and explanatory variables used in this study are outlined in Table 1.

Following Mare (2015), we develop a three-stage estimation framework in which the selected sets of micro and macro explanatory variables are estimated separately and then jointly. In our model, the dependent binary variable is equal to 1 for banks that did not survive over time due to both "financial and strategic exit" (as in Chiorazzo et al. 2018). In further estimates, we run separate estimates considering only the individual types of exits mentioned above.

We classify as cases of financial exit those banks that disappeared due to bankruptcy or liquidation, or that – according to the classification of bank status available in Bankscope and BankFocus – were dissolved without any information on the underlying reasons. We also included in this group of exits those banks that disappeared due to mergers or takeovers which, in the absence of specific information, could have been aimed at rescuing troubled banks (Arena 2008). In the latter case, mergers/takeovers of small banks would represent a market solution to a situation in which a bank found itself in a possible condition of financial distress. Conversely, a bank involved in a business aggregation could be healthy *per se*, at least in the short run, but see a strategic option in the merger/acquisition transaction to avoid, for example, future fragilities due to more accentuated competitive local arenas (strategic exit).

Within the empirical literature, an identification strategy commonly used to define distressed and then merged banks (e.g., Gonzales-Hermosillo 1999; Betz et al. 2014) is the coverage ratio (computed as capital equity and loan reserves minus non-performing loans to total assets). Banks dissolved due to mergers or takeovers are classified as distressed or, equivalently, in a state of financial exit if their coverage ratio is less than zero before the merger/takeover. With it being impossible to use, as in Betz et al. (2014), an indicator such as the coverage ratio due to the limited availability of data on impaired loans in our sample, we relied on the Z-score index as an alternative and widely employed identification tool. The Z-score is an accounting-based indicator of banks' distance to default (Poghosyan and Čihak 2011; Vazquez and Federico 2012; Chiaramonte et al. 2015). Its empirical attractiveness rests on the fact that it does not require strong assumptions about the distribution of returns on assets (Roy 1952; Boyd and Graham 1986; Strobel 2011), other than the ability to use accounting data − which are generally widely available − for its computation. We calculated individual bank Z-scores as the sum of the pre-tax or gross return on assets (ROA) and the equity to total assets ratio over the three-year rolling standard deviation of pre-tax ROA (Chiaramonte et al. 2015). We used the gross ROA since taxation on bank profits is set at different rates in the various countries in our sample, thus affecting net profitability. Banks dissolved by mergers/takeovers are therefore classified as being in a state of financial distress if their annual Z-score lies in the first quartile of the sample distribution in the year preceding their exit. By contrast, those banks involved in business combinations that have a higher Z-score are classified as disappeared for strategic purposes.

2.2. Explanatory variables

Following Betz et al. (2014), we employ two sets of explanatory variables: those expressing the bank-specific vulnerability and related to the individual bank's financial statement, and those representing sources of local and country-specific vulnerability factors, e.g., macro-economic imbalances and socio-demographic traits that could affect the disciplinary power of the market over time.

As regards the bank-specific independent variables, we use the size of the bank (*Size*), approximated by the natural logarithm of total assets (in millions of euros), to capture possible scale effects (i.e., diversification, managerial know-how, external monitoring, etc.). Demsetz and Strahan (1997) established that increases in banks' total assets reduce firm-specific risk and are positively related to diversification. Similarly, Stiroh (2004) and Mercieca et al. (2007) stated that larger banks take fewer risks as bank size increases. Hakenes and Schnabel (2011) provided evidence that the implementation of the Basel II regulations drove smaller banks to take on more risk compared to larger banks because the latter have the option to choose between the Standardized and Internal Ratings Approaches. On these grounds, we hypothesize a negative relationship between the size and probability of exit of the banks in our sample.

An individual bank's capacity to absorb losses is approximated by the *Capital* variable, calculated as the ratio between equity and total assets as a percentage. Capital buffers lower the banks' likelihood of default (Shim 2013) and risks (Barra and Ruggiero 2021). Therefore, we assume a negative relationship between the level of capitalization and the probability of exit of the banks in our sample.

The *Funding gap* variable aims to proxy primarily individual banks' exposure to liquidity risk. It is calculated as the ratio of net

Table 1
Variables description. This table reports variable definitions, data sources, and representative studies.

Variable	Definition and source	Source	Representative studies
Dependent Variables			
Event	Binary variable taking a value of 1 if a bank entered a financial or strategic exit, 0 otherwise.	Own calculations using data from BankScope and BankFocus.	
Financial exit	Binary variable taking a value of 1 if a bank entered a financial exit, 0 otherwise. Financial exit occurs when a bank goes bankrupt or is liquidated or dissolved without any further information. This status also includes banks dissolved due to merger or take-over and whose annual Z-score is in the first quartile of the sample distribution in the year preceding the bank's disappearance.	Own calculations using data from BankScope and BankFocus.	
Strategic exit	Binary variable taking a value of 1 if a bank entered a strategic exit, 0 otherwise. Strategic exit occurs when a bank disappears due to a merger or take-over and whose annual Z-score is in the second or higher quartile of the sample distribution in the year preceding the bank's disappearance.	Own calculations using data from BankScope and BankFocus.	
Bank-specific variables			
Size	Natural logarithm of total assets (in millions of euros).	Own calculations using data from BankScope and BankFocus.	Berger and Bouwman (2013); Chernykh (2014); Mare (2015); Clark et al. (2018); Barth et al. (2023)
Capital	Equity is divided by total assets in percentage.	BankScope and BankFocus.	DeYoung et al. (2004); Chernykh (2014); Mare (2015); Chiorazzo et al. (2018); Barth et al. (2023)
Funding gap	Net customer loans are divided by customer deposits.	Own calculations using data from BankScope and BankFocus.	Mare (2015); Chiorazzo et al. (2018)
Credit risk	Loan loss provisions are divided by total assets in percentage.	Own calculations using data from BankScope and BankFocus.	Mare (2015); Contreras et al. (2023)
RAROA	Annual risk-adjusted return on assets (RAROA). The latter is computed as the 3-year moving average of the gross annual return on assets (ROA) over the corresponding moving standard deviation of ROA.	Own calculations using data from BankScope and BankFocus.	Mercieca et al. (2007); Turk Ariss (2010); Clark et al. (2018)
Cost to income	Operating expenses as a share of the sum of net-interest revenue and other operating income in percentage.	BankScope and BankFocus.	Maggiolini and Mistrulli (2005); Poghosyan and Čihak (2011); Liu et al. (2013); Mare (2015); Chiaramonte et al. (2015); Pappas et al. (2017)
Income div	Non-interest income as a share of the sum of net-interest revenue and other operating income in percentage.	BankScope and BankFocus.	Stiroh (2004); Stiroh and Rumble (2006); Chiaramonte et al. (2015); Pappas et al. (2017); Chiorazzo et al. (2018)
Macroeconomic variables			
Monetary policy	Annual residuals from a regression of the 3-month interbank rate on national real GDP growth rate and inflation.	Own calculations from data collected from the European Central Bank (ECB), Eurostat, and International Monetary Fund (IMF).	Molyneux et al. (2019); Caselli et al. (2020)
Concentration	Annual national Herfindahl-Hirschman Index (HHI) divided by 100.	European Central Bank (ECB).	Beck et al. (2013)
Unemployment	Annual unemployment rate from 15 to 74 years old (NUTS 2 figures).	Eurostat	Kočenda and Iwasaki (2022); Liu et al. (2013)
Tertiary education	Annual percentage of the population aged 25–64 years with tertiary education (levels 5–8) (NUTS 2 figures).	Eurostat	OECD (2021)
Elderly population	Annual percentage of the population aged 65 and over to the total population (NUTS 2 figures).	Eurostat	McFadden (2008); OECD (2021)
Population density	Annual thousands of inhabitants per square kilometer (NUTS 2 figures).	Eurostat	Ostergaard et al. (2016)
Contagion	Dummy variable equal to 1 when another small bank in the same region (NUTS 2 level) disappeared in the last 12 months and 0 otherwise.	Own calculations using data from BankScope and BankFocus.	Poghosyan and Čihak (2011)

Table 2
Sample composition. This table shows the estimation sample distribution by bank status (active banks versus disappeared banks) and size (in millions of euros) for each European country. The sample period is from 2005 to 2022.

	Active banks				Disappeared banks			
Country	<250	250 – 1000	1000 – 5000	Total	<250	250 – 1000	1000 – 5000	Total
Austria	225	146	32	403	114	42	5	161
Belgium	1	7	8	16	1	4	5	10
Bulgaria	2	5	5	12	0	0	1	1
Croatia	4	7	3	14	2	0	1	3
Cyprus	12	8	4	24	0	1	1	2
Czech Republic	0	2	7	9	0	0	2	2
Denmark	18	13	10	41	2	2	4	8
Estonia	3	1	1	5	1	0	0	1
Finland	78	34	16	128	33	4	3	40
France	13	27	31	71	7	10	10	27
Germany	381	442	342	1,165	229	214	47	490
Greece	0	2	2	4	0	1	1	2
Hungary	2	7	3	12	1	0	2	3
Ireland	9	0	0	9	0	0	0	0
Italy	133	122	58	313	140	81	52	273
Latvia	6	1	5	12	1	1	1	3
Lithuania	0	1	2	3	1	1	0	2
Luxembourg	5	15	13	33	9	6	7	22
Malta	4	3	2	9	0	1	0	1
Netherlands	0	1	7	8	0	1	0	1
Poland	108	5	8	121	3	1	1	5
Portugal	68	19	6	93	9	1	2	12
Romania	1	5	6	12	1	1	0	2
Slovak Republic	1	2	2	5	0	1	3	4
Slovenia	0	2	8	10	0	1	5	6
Spain	34	26	22	82	8	4	11	23
Sweden	21	31	18	70	0	0	0	0
Total	1,129	934	621	2,684	562	378	164	1,104
Of which								
Commercial	129	173	185	487	42	52	99	193
Cooperatives	932	611	179	1,722	512	270	43	825
Savings	68	150	257	475	8	56	22	86
Financial exit estimation	1,092	917	614	2,623	176	130	92	398
Strategic exit estimation	1,114	919	601	2,634	386	248	72	706
2005–2012	827	922	564	2,313	101	77	45	223
2013–2022	1,096	914	610	2,620	461	301	119	881

customer loans to customer deposits (e.g., Mare 2015; Chiorazzo et al. 2018). Given that deposits are usually considered a more stable funding source than the interbank market or securities funding, a lower *Funding gap* is expected to be negatively associated with the probability of bank disappearance. An increasing *Funding gap* reveals that those banks finance their illiquid assets, such as customer loans, with sources other than deposits, which substantially increases their liquidity risk. Indeed, a higher *Funding gap* increases the bank's dependence on so-called market-based financing which carries comparatively higher costs than those associated with customer deposits. Thus, the *Funding gap* may also proxy for the exposure to interest rate risk.

We proxy asset quality through the ratio of loan loss provisions to total assets as a percentage (*Credit risk*). A higher proportion of loan loss provisions to total assets is expected to increase the probability of disappearance, for instance, due to distress. However, the effect of provisioning is potentially ambiguous: whereas higher loan loss provisions could proxy for higher expected losses, they may be an accounting device for earning and capital management (e.g., Kanagaretnam et al. 2004; Jin et al. 2018; Tran et al. 2020; Contreras et al. 2023).

We look at individual bank risk and follow Mercieca et al. (2007), Turk Ariss (2010), and Clark et al. (2018) in computing a risk-adjusted performance measure, the risk-adjusted return on assets (*RAROA*). The latter is calculated as the three-year moving average of the annual gross ROA divided by the corresponding moving standard deviation of gross ROA. Higher values of *RAROA* indicate higher profitability per unit of earning volatility, thus lowering exposure to the risk of exit.

The managerial quality of the bank is approximated by the cost to income ratio, *Cost to income*, (e.g., Poghosyan and Čihak 2011; Mare 2015; Chiaramonte et al. 2015; Pappas et al. 2017). This is calculated as operating expenses (e.g., staff and administrative costs) divided by the sum of net interest revenue and other operating income. Higher values denote higher managerial inefficiency, thus leading to a decrease in the probability of bank survival.

Finally, to account for the level of income diversification we include a variable (*Income div*) calculated as non-interest income over interest and non-interest operating revenues. The traditional business model of small banks relies mainly on borrowing and lending; therefore, we can expect a prevalence of interest income over operating revenues (Chiorazzo et al. 2018). In a classical à la Markowitz framework, the emergence of fee-based streams of revenues can generate diversification benefits; however, as stated by Stiroh and Rumble (2006), when the high volatility characterizing these incomes offsets the beneficial effect of covariance, the final effect on the

Table 3
Descriptive Statistics. This table reports summary statistics on micro and macroeconomic explanatory variables as described in Table 1 for active and disappeared banks over the period 2005–2022. The column "Diff in means" reports the value of the mean-comparison tests in which the null hypothesis is that the means of the two groups (active and disappeared banks) are equal. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

	Active banks		Disappeared banks		*Diff in means*
	Mean	St.Dev.	Mean	St.Dev.	
Size (Ln)	6.266	1.216	5.777	1.148	*0.488****
Capital (%)	9.908	5.280	8.985	4.536	*0.924****
Funding gap	0.989	1.333	1.093	1.395	*−0.104****
Credit risk (%)	0.211	0.527	0.420	0.731	*−0.209****
RAROA	6.595	8.397	4.950	7.858	*1.645****
Cost to income (%)	70.500	15.389	62.271	29.460	*8.230****
Income div (%)	31.609	16.089	30.715	13.518	*0.894****
Monetary policy	−0.111	0.371	−0.148	0.390	*0.0370****
Concentration	4.835	4.254	4.094	3.299	*0.741****
Unemployment (%)	6.045	4.412	6.417	4.119	*−0.372****
Tertiary education (%)	27.760	7.962	24.597	7.820	*3.163****
Elderly population (%)	20.353	2.472	20.196	2.312	*0.158****
Population density	0.337	0.635	0.365	0.758	*−0.0280***
Number of banks	2,684		1,104		

overall profitability of a bank can be negative. Hence, in line with Chiaramonte et al. (2015) the expected sign of the coefficient associated with the variable *Income div* on bank disappearance is unclear.

To capture the effect of the macroeconomic and social context on the disappearance of small banks, several variables have been selected, preferably having a local dimension where possible, given the limited geographic operations of small banks and their strong dependence on local conditions.

To proxy the effects of monetary policy shocks on small bank exit we follow, among others, Caselli et al. (2020) and compute the Taylor rule residuals (Taylor 1993), since in our empirical set-up most of the countries are characterized by identical monetary policy rates but different economic conditions in terms of real GDP growth and inflation. The explanatory variable (*Monetary Policy*) is built using annual country data on the three-month interbank interest rate (%) collected from Eurostat and the European Central Bank regressed on the real GDP growth (%) from the International Monetary Fund, and the inflation rate (%) from the European Central Bank. Taylor rule residuals are estimated with a Panel Least Squares (PLS) regression for the eurozone economies and via a separate OLS regression for the other economies. Residuals depict the unexplained component of fluctuations in monetary policy rates (Brissimis et al. 2014) while accounting for cross-sectional variation in monetary conditions (Maddaloni and Peydró 2013). Positive (or negative) Taylor rule residuals denote a tight (or loose) monetary environment. According to the theoretical foundations of the risk-taking channel (e.g., Borio and Zhu 2012; Angeloni et al. 2015), looser monetary conditions prompt banks to operate closer to default (Molyneux et al. 2019; Caselli et al. 2020) and *vice versa*. Given that small banks' profitability tends to depend strongly on the interest margin, we can expect more restrictive monetary policies to improve bank interest margins (Alessandri and Nelson 2015; Borio and Gambacorta 2017; Claessens et al. 2018) and therefore the resilience of these banks to distress phenomena that may also result in M&A transactions mainly aimed at rescuing troubled banks. However, it has been noted that looser monetary policy can also exert a positive influence on banks' profitability and stability. This happens through different channels, including lower borrowing rates, sounder overall economic outlook – which can reduce NPLs and enhance lending opportunities – and a growth in the value of assets, including government and corporate bonds (Demertzis and Wolff 2016; Altavilla et al. 2018; Lopez et al. 2020; Altavilla et al. 2022). Therefore, the expected effect of monetary policy on banks' disappearance is controversial and needs to be empirically determined.

To evaluate the role of competition on the fragility/stability of sample banks in line with the competition-fragility view (Marcus 1984; Keeley 1990; Diallo 2015) versus the competition-stability view (Boyd and De Nicolò 2005; De Nicolò and Lucchetta 2009; Schaeck et al. 2009), we employ the variable *Concentration*. Unfortunately, there is no valid measure of competition at the local level for our specific sample and therefore we use an indicator of concentration, such as the Herfindahl-Hirschman Index (HHI) at the country level. Despite the theoretical meaning of the competition-fragility view which identifies the increase in the degree of competition as the cause of banks' greater fragility (e.g., Beck et al. 2013), it seems useful to us to observe that higher degrees of concentration in the national banking system may expose small banks to greater competitive pressures from large banks in their local environment, which erode their profits and/or push them to take on higher levels of risk, thus ultimately leading to an increased probability of exit. Stakeholder-oriented banks, such as cooperative and savings banks, can however be less exposed to such pressures, given their not-for-profit orientation (e.g., Ayadi et al. 2009; Ayadi et al. 2010). On the other hand, as bank market power increases at the national level, the riskiness of the credit portfolios held by large banks may rise, thus leaving room for them to disengage from lending activity, especially from more opaque retail lending. This can favor the activity and survival of small banks if they are willing to make greater investments in collecting information, screening, and monitoring (Clark et al. 2018). The effect of the degree of national concentration on the disappearance of small banks is therefore uncertain.

Additionally, we consider the unemployment rate (*Unemployment*) at the regional level, which can impact economic growth at a local level and ultimately the creditworthiness of bank borrowers. The literature based on U.S. and European banks shows that various

Table 4

Main estimates – full sample. This table shows in Panel A the complementary log–log model estimations obtained by regressing bank exit on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. The explanatory dummy variable Contagion is added in some specifications and is described in Table 1. The sample period is 2005–2022. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%; out-of-sample predictions are calculated on a training sample over the period 2005–2017 and a hold-out period covering the years 2018–2022. Further out-of-sample predictions are calculated on a training sample consisting of banks located in Austria, Germany, and Italy and a hold-out sample consisting of banks in the remaining countries. For both out-of-sample predictions, only those with a 3% cut-off are presented. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the whole period and out-of-samples. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A

	Model 1	Model 2	Model 3	Model 4	Model 5
L.Size	−0.275****	−0.284****			−0.294****
	(0.027)	(0.028)			(0.029)
LCapital	−0.052****	−0.053****			−0.056****
	(0.009)	(0.010)			(0.010)
L.Funding gap	0.048***	0.043**			0.0416*
	(0.016)	(0.018)			(0.022)
L.Credit risk	0.458****	0.453****			0.417****
	(0.045)	(0.047)			(0.051)
L.RAROA	−0.008	−0.008			−0.007
	(0.005)	(0.005)			(0.005)
L.Cost to income	0.020****	0.020****			0.021****
	(0.002)	(0.002)			(0.002)
L.Income div	0.006***	0.005**			0.005**
	(0.002)	(0.002)			(0.002)
L.Monetary policy			−0.284**	−0.262	−0.276*
			(0.117)	(0.191)	(0.159)
L.Concentration			0.005	0.0178**	0.018***
			(0.008)	(0.008)	(0.009)
L.Unemployment			0.019**	0.037****	0.006
			(0.007)	(0.008)	(0.009)
L.Tertiary education			−0.001	−0.010*	−0.005*
			(0.005)	(0.005)	(0.006)
L.Elderly population			0.030**	0.035**	0.056**
			(0.014)	(0.017)	(0.018)
L.Population density			0.079*	0.096**	0.093*
			(0.044)	(0.048)	(0.056)
Contagion		1.604****		1.683****	1.633****
		(0.0713)		(0.072)	(0.073)
Year dummies	Yes	Yes	Yes	Yes	Yes
No. of disappeared banks	1,104	1,104	1,104	1,104	1,104
No. of banks	3,788	3,788	3,788	3,788	3,788
Mean hazard of disappeared banks					0.089
Mean hazard					0.031
No. of obs	35,033	35,033	35,033	35,033	35,033

Panel B

	Model 1	Model 2	Model 3	Model 4	Model 5
In-sample predictions 1 % cut-off (%)					
Sensitivity	95.83	91.76	99.91	95.47	91.49
Specificity	9.94	32.65	0.34	18.06	33.43
Corr. classified	12.65	34.51	3.48	20.50	35.26
ROC area	52.89	62.20	50.13	56.77	62.46
In-sample predictions 2 % cut-off (%)					
Sensitivity	84.51	79.80	86.32	74.82	62.46
Specificity	39.46	79.80	27.68	63.62	61.38
Corr. classified	40.88	62.09	29.52	63.98	61.96
ROC area	61.98	70.66	57.00	69.22	70.50
In-sample predictions 3 % cut-off (%)					
Sensitivity	66.49	73.91	68.03	71.83	73.64
Specificity	63.48	69.35	53.08	68.94	69.61
Corr. classified	63.58	69.49	53.55	69.03	69.74
ROC area	64.98	71.63	53.55	70.39	71.63
In-sample disappeared banks ranking by decile of the hazard rate (%)					

(continued on next page)

Table 4 (*continued*)

Panel B	Model 1	Model 2	Model 3	Model 4	Model 5
1–5 decile	23.37	14.95	29.89	17.66	15.22
6	7.70	5.25	11.68	5.89	5.16
7	9.24	8.24	10.78	7.34	6.97
8	10.96	11.41	14.13	16.30	12.05
9	14.49	16.85	15.40	19.93	17.30
10	34.24	43.30	18.12	32.88	43.30
Out-of-sample predictions 3 % cut-off (hold-out sample 2018–2022) (%)					
Sensitivity	33.56	60.50	0.00	70.73	59.13
Specificity	83.54	78.26	100.00	67.50	78.72
Corr. classified	81.80	77.64	96.51	67.61	78.04
ROC area	58.55	69.38	50.00	69.11	68.92
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample 2018–2022) (%)					
1–5 decile	33.56	16.89	52.99	19.23	18.51
6	7.53	5.02	9.83	5.34	4.63
7	10.27	8.45	8.76	13.68	7.20
8	10.96	15.07	10.47	15.81	14.40
9	12.56	17.58	7.26	18.80	16.97
10	25.11	36.99	10.68	27.14	38.30
Out-of-sample prediction 3 % cut-off (hold-out sample with countries other than Austria, Germany, and Italy) (%)					
Sensitivity	55.49	59.34	83.71	70.45	52.78
Specificity	54.73	73.64	13.64	54.31	75.44
Corr. classified	54.76	73.21	15.68	54.78	74.76
ROC area	55.11	66.49	48.68	62.38	64.11
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample with countries other than Austria, Germany, and Italy, (%)					
1–5 decile	41.21	26.92	50.76	26.14	29.44
6	9.89	7.69	10.98	15.53	7.22
7	10.99	3.85	6.06	9.47	6.67
8	12.09	8.24	6.06	5.30	10.00
9	8.24	15.93	9.09	14.02	15.56
10	17.58	37.36	17.05	29.55	31.11

proxies for economic development (such as unemployment, stock market volatility, GDP growth, real estate investment, etc.) improve predictions of bank distress (Liu et al. 2013; Kočenda and Iwasaki 2022). We expect a positive relationship between *Unemployment* and bank exit.

In line with the analysis by Ostergaard et al. (2016) on the factors determining the survival of Norwegian savings banks, we include some variables that approximate local human capital and its ability to strengthen/weaken the resilience of small banks. Following Coleman (1988), we adopt the notion that human capital is created by changes in personnel that generate skills and capabilities that enable the bank to act in new ways, e.g., by promoting economic development, fostering monitoring of economic and financial activities, etc. Human capital increases with general training and knowledge and tends to depreciate with age (McFadden 2008; OECD 2021). To this end, we have selected two variables, which respectively approximate, at the local level, the prevalence in the population of advanced education qualifications (*Tertiary education*) and the proportion of older citizens aged 65 and over (*Elderly population*). Regarding the *Tertiary education* variable, we hypothesize that a more widespread distribution of higher education could favor the survival of small banks, especially if it benefits local economic development and improves the stakeholders' ability to monitor and discipline the management of financial intermediaries. Higher levels of educational attainment can also help stimulate the adoption of best practices in banking risk management, thus improving bank resilience. By contrast, we are led to hypothesize that as the share of the elderly population increases, the survival of small banks is more at risk, because, in the long run, the contributions that human capital can make to local development and the stability of the existing organizations may gradually decrease.

Moreover, following Ostergaard et al. (2016), we control for the thousands of inhabitants per square kilometer (*Population density*), which may exert divergent effects on bank survival. Since the supply of banking services in areas with low population density tends to raise banking costs, the survival of banks located in such areas may be more at risk (Dietsch and Lozano-Vivas 2000). On the other hand, increasing population density may, for instance, boost competitive pressures or help to spread contagion effects among local banks. Therefore, the expected effect of this covariate on small banks' disappearance is uncertain.

Finally, we control for another variable which is aimed at capturing contagion between banks, in line with the empirical contributions of Hardy (1998) and Poghosyan and Čihak (2011). We construct the variable *Contagion* as a dummy assuming a value of 1 when another small bank in the same region (NUTS 2 level) exited in the last 12 months due to both financial and strategic exit, and zero otherwise. Given how geographically limited the territories taken into consideration (NUTS 2 level) are, the exit of one or more small banks is more likely to occur in the event of adverse macroeconomic local and national shocks. To evaluate the contribution of the variable *Contagion* we will run separate estimations. It is worth noting that the disappearance of small banks in limited geographical areas may generate rumors more easily and give rise to bank-run phenomena that may trigger financial exits. On the other hand, the increase in cases of strategic exit at a local level can stimulate emulative behaviors among local small banks fearing for their future survival.

Table 5

Estimates by bank size. This table shows in Panel A the complementary log–log model estimations for different bank sizes obtained by regressing bank exit on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. The sample period is 2005–2022. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%; out-of-sample predictions are calculated on a training sample over the period 2005–2017 and a hold-out period covering the years 2018–2022. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the whole period and out-of-sample. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A	Assets < 250 (mln €)	250 (mln €) <= Assets < 1000 (mln €)	1000 (mln €) <=Assets <= 5000 (mln €)
L.Size	−0.392****	−0.362***	0.036
	(0.083)	(0.139)	(0.177)
L.Capital	−0.051****	−0.109****	−0.006
	(0.012)	(0.021)	(0.024)
L.Funding gap	0.068*	−0.065	0.071**
	(0.040)	(0.041)	(0.028)
L.Credit risk	0.358****	0.464****	0.195
	(0.093)	(0.098)	(0.121)
L.RAROA	−0.003	0.002	−0.053**
	(0.008)	(0.007)	(0.022)
L.Cost to income	0.026****	0.022****	0.012***
	(0.003)	(0.004)	(0.005)
L.Income div	−0.003	0.003	−0.002
	(0.008)	(0.004)	(0.005)
L.Monetary policy	−0.518**	−0.227**	−0.863**
	(0.243)	(0.102)	(0.392)
L.Concentration	0.011	0.012	0.046**
	(0.013)	(0.018)	(0.018)
L.Unemployment	−0.011	0.012*	0.084****
	(0.013)	(0.018)	(0.016)
L.Tertiary education	−0.023**	0.001	−0.003
	(0.010)	(0.010)	(0.012)
L.Elderly population	0.090***	0.081***	0.041
	(0.028)	(0.028)	(0.040)
L.Population density	0.108	0.030	0.115*
	(0.163)	(0.087)	(0.067)
Contagion	1.820****	1.750****	1.346****
	(0.115)	(0.134)	(0.179)
Year dummies	Yes	Yes	Yes
No. of disappeared banks	482	420	202
No. of banks	1,611	1,354	823
Mean hazard of disappeared banks	0.028	0.068	0.031
Mean hazard	0.013	0.028	0.016
No. of obs.	11,442	12,686	9,519

Panel B	Assets < 250 (mln €)	250 (mln €) <= Assets < 1000 (mln €)	1000 (mln €) <=Assets <= 5000 (mln €)
In-sample predictions 1 % cut-off (%)			
Sensitivity	94.74	92.64	86.11
Specificity	24.78	42.90	50.31
Corr. classified	27.69	44.44	50.98
ROC area	59.76	67.77	68.21
In-sample predictions 2 % cut-off (%)			
Sensitivity	85.47	83.25	70.00
Specificity	55.02	65.79	72.12
Corr. classified	56.28	66.33	72.08
ROC area	70.25	74.52	71.06
In-sample predictions 3 % cut-off (%)			
Sensitivity	81.47	76.65	51.67
Specificity	64.78	72.43	83.45
Corr. classified	65.47	72.56	82.84
ROC area	73.12	74.54	67.56
In-sample disappeared banks ranking by decile of the hazard rate (%)			

(*continued on next page*)

Table 5 (*continued*)

Panel B	Assets < 250 (mln €)	250 (mln €) <= Assets < 1000 (mln €)	1000 (mln €) <=Assets <= 5000 (mln €)
1–5 decile	13.26	9.90	13.89
6	4.21	4.57	6.11
7	8.42	7.87	8.89
8	10.53	11.93	15.56
9	19.37	19.80	17.22
10	44.21	45.94	38.33
Out-of-sample predictions 3 % cut-off (hold-out sample 2018–2022) (%)			
Sensitivity	47.81	75.17	36.47
Specificity	76.73	60.21	73.89
Corr. classified	75.23	60.68	73.13
ROC area	62.27	67.69	55.18
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample 2018–2022) (%)			
1–5 decile	16.75	18.11	22.22
6	6.70	3.15	2.78
7	11.96	8.66	22.22
8	13.88	22.05	15.28
9	16.75	14.96	15.28
10	33.97	33.07	22.22

2.3. Sample and descriptive statistics

The sample consists of 3,788 small banks headquartered in 27 European countries (Table 2).

In our study, we classify as a "small bank" a credit institution with total assets not exceeding 5 billion euros, consistent with article 4 (1), point 145 of EU Regulation No 575/2013, which sets this threshold for small and non-complex entities. This definition has also been adopted by the European Banking Authority in line with its Guidelines on common procedures and methodologies for the Supervisory Review and Evaluation Process (SREP). The EU Single Resolution Board has also recently revised its resolution procedures (Guidance on the Liability Data Report 2023), defining organizations with total assets exceeding 5 billion euros as a "relevant legal entity". Therefore, credit institutions with total assets lower than the afore-mentioned threshold are not "relevant", even if they belong to a banking group that can be subject to resolution rules. To verify the factors that determine the disappearance of small banks of various sizes, three further sub-samples are identified, respectively comprising banks with assets of less than 250 million euros, those with assets of between 250 million and 1,000 million euros, and those with over 1,000 million but less than 5,000 million euros.

During the period of analysis, 2,684 banks were continuously active, and 1,104 disappeared, as a result of both financial and strategic exits.

Most of the banks in the sample (approximately three-quarters) are concentrated in just three countries: Austria, Italy, and Germany. The latter has 1,655 banks, almost half of the total. Banks with total assets of less than 1,000 million euros account for 79.3 % of the total number of banks. Since we report the post-estimation statistics, for some countries no cases of bank disappearance are available, even though they are present in the original sample. Among the non-surviving banks (29.1 % of the total sample), about 85 % have total assets below 1 billion euros.

The bottom lines of Table 2 show the composition of the sample for all the further sub-sample analyses and robustness checks performed.

As displayed in Table 3, the results relating to all the covariates are statistically different for active and disappeared banks: the former are bigger, more capitalized, have a lower funding gap and credit risks, higher risk-adjusted profitability, and follow a more diversified business, despite being less managerially efficient. The disappeared banks operate in environments with higher unemployment rates, less educated populations, a lower population age, less concentrated national banking systems, and higher Taylor rule residuals and population density.

3. Main findings

3.1. Baseline estimation results

Table 4 shows our model estimates for the entire sample of banks analyzed.

The first two columns contain the results of the analysis performed using only microeconomic variables as explanatory variables for our dependent variable (*Event)*. The results show that several covariates make a significant contribution to determining the disappearance of small banks over the period examined.

The Model 1 column reports the results of the estimates using only balance sheet data from the surveyed banks as explanatory

Table 6

Estimates by business model. This table shows in Panel A the complementary log–log model estimations for different bank business models obtained by regressing bank exit on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. The sample period is 2005–2022. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%; out-of-sample predictions are calculated on a training sample over the period 2005–2017 and a hold-out period covering the years 2018–2022. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the whole period and out-of-sample. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A

	Commercial banks	Cooperative banks	Savings banks
L.Size	0.109	−0.338****	−0.546****
	(0.072)	(0.038)	(0.116)
L.Capital	−0.013	−0.062****	−0.150***
	(0.011)	(0.0139)	(0.055)
L.Funding gap	0.021	0.031	0.062
	(0.022)	(0.078)	(0.103)
L.Credit risk	0.162*	0.415****	0.913**
	(0.087)	(0.079)	(0.396)
L.RAROA	−0.081****	0.002	−0.011
	(0.025)	(0.005)	(0.025)
L.Cost to income	0.007**	0.030****	0.045****
	(0.003)	(0.004)	(0.010)
L.Income div	−0.0006	0.009**	0.007
	(0.003)	(0.003)	(0.012)
L.Monetary policy	−0.156	−0.423*	−1.020
	(0.176)	(0.225)	(0.971)
L.Concentration	0.034**	0.003	0.0341
	(0.015)	(0.011)	(0.032)
L.Unemployment	0.043**	−0.011	0.078
	(0.018)	(0.012)	(0.052)
L.Tertiary education	−0.019	0.0002	−0.004
	(0.012)	(0.007)	(0.031)
L.Elderly population	0.060	0.061***	0.224***
	(0.037)	(0.021)	(0.070)
L.Population density	0.052	0.203*	0.283*
	(0.060)	(0.110)	(0.171)
Contagion	1.383****	1.671****	2.144****
	(0.171)	(0.089)	(0.332)
Year dummies	Yes	Yes	Yes
No. of disappeared banks	193	825	86
No. of banks	680	2,547	561
Mean hazard of disappeared banks	0.071	0.034	0.059
Mean hazard	0.040	0.014	0.012
No. of obs	4,700	24,076	6,232

Panel B

	Commercial banks	Cooperative banks	Savings banks
In-sample predictions 1 % cut-off (%)			
Sensitivity	98.96	93.33	82.56
Specificity	15.24	33.88	70.71
Corr. classified	18.68	35.92	70.88
ROC area	57.10	63.61	76.64
In-sample predictions 2 % cut-off (%)			
Sensitivity	89.64	82.79	70.93
Specificity	42.22	59.05	84.23
Corr. classified	44.17	59.86	84.05
ROC area	65.93	70.92	77.58
In-sample predictions 3 % cut-off (%)			
Sensitivity	77.72	77.70	60.47
Specificity	59.68	67.98	89.77
Corr. classified	60.43	68.31	89.36
ROC area	68.70	72.84	75.12
In-sample disappeared banks ranking by decile of the hazard rate (%)			
1–5 decile	13.47	13.58	9.30
6	11.92	4.85	5.81

(*continued on next page*)

Table 6 (*continued*)

Panel B	Commercial banks	Cooperative banks	Savings banks
7	8.29	7.27	2.33
8	13.99	11.52	8.14
9	16.06	16.97	16.28
10	36.27	45.82	58.14
Out-of-sample predictions 3 % cut-off (hold-out sample 2018–2022) (%)			
Sensitivity	80.65	43.38	68.75
Specificity	44.74	84.16	78.58
Corr. classified	46.53	82.57	78.44
ROC area	62.69	63.77	73.67
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample 2018–2022) (%)			
1–5	22.39	17.42	42.90
6	13.43	4.80	28.60
7	7.46	8.41	14.30
8	16.42	13.51	0.00
9	10.45	19.22	0.00
10	29.85	36.64	14.30

variables. Reported coefficients are not exponentiated to obtain hazard ratios.[2] All covariates, with the exception of *RAROA,* appear significant, albeit with different signs. Larger (Maggiolini and Mistrulli 2005; Mare 2015) and well-capitalized banks (Betz et al. 2014; Mare 2015) are less exposed to market exit (measured by the variable *Event*). In contrast, banks with higher credit risk (Mare 2015; Chiorazzo et al. 2018), higher managerial inefficiency (Chiorazzo et al. 2018), higher loan-to-deposit ratios, and higher exposure to non-interest incomes (Stiroh 2004) are more prone to disappear. Overall, the results are not surprising: however, some relationships appear directly related to the period under analysis. In fact, during the period under observation, the squeezing of banks' margins resulting from the outbreak of various crises (sub-prime, sovereign debt, COVID-19), coupled with an unprecedented reduction in interest rates, made the pursuit of efficiency and the containment of credit risks essential. Banks with a high exposure to customer lending and a low ability to raise money from the public savings certainly faced more critical issues during the period analyzed; smaller size proved an additional element of weakness, partly due to the need to be of adequate scale to be able to proceed with effective product and service diversification processes.

The Model 2 column of Table 4 provides the results of estimating the basic model using the microeconomic explanatory variables just described but adding the variable *Contagion*. The underlying idea behind this choice is that the disappearance of small banks in a given geographical area represents the synthesis of critical elements that are manifesting themselves; this is compounded by small banks potentially suffering a stigma effect, that could lead to the disappearance of other intermediaries. As in Poghosyan and Čihak (2011), we find that the existence of more than one case of small bank disappearance in the region where the sample banks are based has an important effect on the market exit of the analyzed banks. Namely, small banks located in regions for which the dummy *Contagion* takes a value equal to 1 have a risk of exit almost 3.97 times higher than that of small banks located in regions without cases of bank exit. The *RAROA* variable remains statistically insignificant in this new specification, while the significance of the remaining bank-specific variables persists.

Model 3 and Model 4 shed light on the contribution of macroeconomic factors in explaining small banks' exits, respectively excluding and including the covariate *Contagion*.

Model 3 shows a negative sign being related to the dynamics of interest rates: hence, an increase in interest rates, consistent with a tighter monetary policy, is associated with a lower risk of small banks disappearing. This result supports the idea that an increase in interest rates raises banks' net interest margin, reducing stress phenomena. The variable related to banking market concentration is not significant in this specification.

In terms of the macroeconomic variables related to the characteristics of the resident population and labor market conditions (proxies for the area's economic health), contributions to the dependent variable are mixed. A higher unemployment rate, an increase in the share of the population being elderly, and higher population density tend to raise the probability of small bank exits occurring. An older population reports less vibrancy in the labor market, which may result in lower output growth and a lesser ability to create wealth. In addition, older customers tend to exhibit more risk-averse characteristics and utilize more basic banking (deposit or investment) instruments.

Adding the variable *Contagion* to this set of macroeconomic covariates (Model 4), *Unemployment* becomes more significant, while the variable *Monetary policy* loses statistical significance. A higher rate of *Unemployment* signals adverse economic conditions in the area; this can reduce the population's capacity for income and wealth accumulation, resulting in a reduced ability to take advantage of banking services (and, for the bank, to raise resources from the area through deposit accounts or offer services with higher value-added

[2] For instance, if we exponentiate the coefficient of the variable *Size* in Model 1, we find a hazard ratio equal to 0.76 which means that the risk of exit for larger banks decreases by 24%. On the contrary, the hazard ratio for the variable *Funding gap* in the same model is equal to 1.049 which implies that the risk of exit increases 5% for larger loans-to-deposit ratio. Therefore, the hazard ratio indicates the change in the risk of disappearance if the variable rises by one unit.

Table 7

Estimates by type of exit. This table shows in Panel A the complementary log–log model estimations for different types of bank exit obtained by regressing bank disappearance on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. The sample period is 2005–2022. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%; out-of-sample predictions are calculated on a training sample over the period 2005–2017 and a hold-out period covering the years 2018–2022. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the whole period and out-of-sample. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A

	Financial exit	Strategic exit
L.Size	−0.054	−0.394****
	(0.051)	(0.035)
L.Capital	−0.045***	−0.046****
	(0.015)	(0.012)
L.Funding gap	0.070***	−0.041
	(0.023)	(0.041)
L.Credit risk	0.321****	0.189***
	(0.080)	(0.071)
L.RAROA	−0.422****	0.014****
	(0.070)	(0.004)
L.Cost to income	0.007**	0.023****
	(0.003)	(0.002)
L.Income div	0.009***	−0.002
	(0.003)	(0.003)
L.Monetary policy	−0.402	−0.178
	(0.286)	(0.189)
L.Concentration	0.0511****	−0.014
	(0.012)	(0.012)
L.Unemployment	0.016	−0.004
	(0.012)	(0.013)
L.Tertiary education	−0.0007	−0.001
	(0.008)	(0.007)
L.Elderly population	0.047*	0.101****
	(0.027)	(0.022)
L.Population density	0.101*	0.001
	(0.060)	(0.111)
Contagion	1.648****	1.682****
	(0.122)	(0.0918)
Year dummies	Yes	Yes
No. of disappeared banks	398	706
No. of banks	3,021	3,340
Mean hazard of disappeared banks	0.067	0.027
Mean hazard	0.009	0.011
No. of obs	34,327	34,635

Panel B

	Financial exit	Strategic exit
In-sample predictions 1 % cut-off (%)		
Sensitivity	84.92	84.56
Specificity	76.11	53.61
Corr. classified	76.21	54.24
ROC area	80.52	69.09
In-sample predictions 2 % cut-off (%)		
Sensitivity	73.62	74.36
Specificity	86.35	70.96
Corr. classified	86.21	71.03
ROC area	79.99	72.66
In-sample predictions 3 % cut-off (%)		
Sensitivity	63.57	66.86
Specificity	90.81	79.21
Corr. classified	90.50	78.96
ROC area	77.19	73.03
In-sample disappeared banks ranking by decile of the hazard rate (%)		
1–5	4.52	13.88
6	2.26	4.82

(*continued on next page*)

Table 7 (*continued*)

Panel B	Financial exit	Strategic exit
7	4.77	6.94
8	8.04	10.48
9	16.08	17.99
10	64.32	45.89
Out-of-sample predictions 3 % cut-off (hold-out sample 2018–2022) (%)		
Sensitivity	66.89	40.83
Specificity	83.15	82.60
Corr. classified	82.97	81.50
ROC area	75.02	61.75
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample 2018–2022) (%)		
1–5	9.82	15.02
6	2.68	6.39
7	2.68	7.99
8	7.14	12.46
9	16.07	21.73
10	61.61	36.42

elements and profitability). Additionally, the variables *Concentration* and *Tertiary education* show statistically significant coefficients, with positive and negative signs respectively. More concentrated national markets appear to lead to an increase in small bank exits at a local level. This outcome (which contradicts the results of Maggiolini and Mistrulli 2005) is in some ways surprising, since in a period of squeezed margins, one might assume that less competitive markets would still allow banks to extract some benefit from dominant positions; however, this role has likely been played by larger banks, which are able to obtain position rents and exploit benefits of scale. From the perspective of supervisory and regulatory policies, this serves as a warning. In fact, over time the authorities have been pushing smaller banks toward aggregation processes, creating the conditions for an increase in the degree of concentration in the financial system; econometric outcomes show that in certain scenarios there are potential risks linked to this strategy, at least as long as players of markedly different sizes compete in the market. The negative sign of *Tertiary education* indicates the presence of individuals with higher educational qualifications, who – given their higher financial literacy – can access more complex services (which are more profitable to the bank) and react more rationally to critical phenomena that may affect the institution (e.g., avoiding bank runs) and ultimately exert a higher degree of discipline on bank management. It is worth noting that the variable *Contagion* is associated with a strongly significant and positive coefficient, suggesting that this covariate provides a noteworthy contribution in explaining small banks' disappearance, even in this novel specification.

The last column of Table 4 (Model 5) shows the results of the analysis of the entire sample of banks using the full set of bank-specific and macroeconomic explanatory variables. Overall, the sign and significance of the coefficients associated with the different covariates do not change from the previously described analyses: only the coefficients associated with *RAROA* and *Unemployment* are not significant from a statistical point of view.

As shown in Table 4, small banks that have disappeared display a higher hazard compared to active ones.

To assess the performance of our models, or in other words, their goodness of fit (as in Fiordelisi and Mare 2013; Betz et al. 2014), we need an evaluation framework that calculates their usefulness in terms of predicting small bank exit. The predictive ability of our models is tested both in- and out-of-sample and reported in Panel B of Table 4. Through these checks, we classify a bank as disappeared if the likelihood of its exit is greater than an optimum cut-off point that we define conservatively and set respectively at equal to 1 %, 2 %, and 3 % for the in-sample predictions. All banks above (or below) that cut-off point are considered as disappeared (or active) banks. Sensitivity quantifies the proportion of disappeared banks that are correctly identified as such. It is worth noting that a higher cut-off point results in a lower number of banks on the list of exited banks, which tends to decrease the Sensitivity of the model or, in other words, increase the so-called Type 1 errors. The latter occur when we classify as active a bank that did not survive.

In our analysis, we also report an indicator of Specificity which measures the ability of the model to correctly classify healthy banks. In this case a higher cut-off point results in a lower number of banks on the list of disappeared banks, which tends to increase the Specificity of the model or, in other words, reduce the so-called Type 2 errors. These occur when we classify as disappeared a bank that did survive or specifically when false alarms of exit are recorded. As policymakers are more concerned about failing to identify bank distress than issuing false alarms, we believe more attention should be given to the model's Sensitivity (e.g., Betz et al. 2014; Chiaramonte et al. 2015).

Finally, we report an indicator proxying the ability of the model to correctly classify disappeared and active banks as a proportion of the total number of banks annually recorded and the area under the receiver operating characteristic (ROC) curve, which measures the overall performance of a binary classifier at the specified cut-off point.

At a 1 % cut-off, all the models, with minor differences, allow us to successfully detect disappeared banks, as demonstrated by the percentage values of the Sensitivity indicator of in-sample tests. However, this comes at the cost of lower Specificity rates and a lesser ability to correctly classify safe and non-surviving banks. Surprisingly, Models 1 and 3 do not exhibit great differences in predictive ability, contrary to Mare (2015) and Betz et al. (2014), thus indicating that the economic and socio-demographic environment in which small banks operate greatly influences the soundness of small banks, independent of their individual financial and economic characteristics. It is worth noting that the inclusion of the variable *Contagion* has a substantial impact on the reduction of Type 2 errors, or in

Table 8

Estimates for the restricted sample consisting of Austria, Germany, and Italy. This table shows in Panel A the complementary log–log model estimations obtained for a restricted sample consisting of Austria, Germany, and Italy by regressing bank exit on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. The sample period is 2005–2022. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%; out-of-sample predictions are calculated on a training sample over the period 2005–2017 and a hold-out period covering the years 2018–2022. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the whole period and out-of-sample. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A

	Model 1	Model 2	Model 3	Model 4	Model 5
L.Size	−0.392****	−0.373****			−0.412****
	(0.030)	(0.031)			(0.033)
L.Capital	−0.091****	−0.086****			−0.087****
	(0.011)	(0.011)			(0.011)
L.Funding gap	0.027	0.014			−0.003
	(0.024)	(0.027)			(0.037)
L.Credit risk	0.559****	0.520****			0.434****
	(0.053)	(0.056)			(0.063)
L.RAROA	−0.007	−0.006			−0.005
	(0.006)	(0.006)			(0.006)
L.Cost to income	0.024****	0.023****			0.024****
	(0.003)	(0.003)			(0.003)
L.Income div	0.007**	0.007**			0.005**
	(0.003)	(0.003)			(0.003)
L.Monetary policy			−0.542	−0.682**	−0.139
			(0.344)	(0.334)	(0.358)
L.Concentration			0.227****	0.135***	0.0301
			(0.042)	(0.0440)	(0.048)
L.Unemployment			0.026***	0.039****	−0.005
			(0.010)	(0.011)	(0.013)
L.Tertiary education			0.017**	−0.002	−0.021**
			(0.008)	(0.008)	(0.009)
L.Elderly population			0.033*	0.074****	0.090****
			(0.017)	(0.020)	(0.021)
L.Population density			−0.024	0.015	0.129
			(0.0646)	(0.073)	(0.078)
Contagion		1.508****		1.665****	1.596****
		(0.081)		(0.083)	(0.084)
Year dummies	Yes	Yes	Yes	Yes	Yes
No. of disappeared banks	924	924	924	924	924
No. of banks	2,805	2,805	2,805	2,805	2,805
Mean hazard of disappeared banks					0.064
Mean hazard					0.023
No. of obs	29,074	29,074	29,074	29,074	29,074

Panel B

	Model 1	Model 2	Model 3	Model 4	Model 5
In-sample predictions 1 % cut-off (%)					
Sensitivity	94.69	92.52	99.78	92.95	92.19
Specificity	16.29	35.05	1.15	25.59	36.78
Corr. classified	18.78	36.87	4.28	27.73	38.54
ROC area	55.49	63.78	50.47	59.27	64.48
In-sample predictions 2 % cut-off (%)					
Sensitivity	83.95	82.75	84.71	77.66	82.10
Specificity	45.49	60.92	31.94	61.53	60.86
Corr. classified	46.70	61.62	33.61	62.04	61.53
ROC area	64.72	71.84	58.32	69.59	71.48
In-sample predictions 3 % cut-off (%)					
Sensitivity	68.76	75.16	63.12	75.49	75.05
Specificity	66.18	69.97	59.51	65.31	70.76
Corr. classified	66.26	70.13	59.63	65.63	70.89
ROC area	67.47	72.56	61.32	70.40	72.91
In-sample disappeared banks ranking by decile of the hazard rate (%)					
1–5	24.79	13.46	27.14	16.94	13.02

(continued on next page)

Table 8 (*continued*)

Panel B	Model 1	Model 2	Model 3	Model 4	Model 5
6	6.20	4.32	9.53	4.52	5.31
7	8.97	6.16	10.20	8.66	6.94
8	9.94	9.68	14.15	16.65	11.39
9	14.32	15.54	17.23	20.69	17.90
10	35.79	35.84	21.75	32.53	45.44
Out-of-sample predictions 3 % cut-off (hold-out sample 2018–2022) (%)					
Sensitivity	37.71	55.87	21.79	76.82	63.41
Specificity	86.83	79.74	85.90	59.09	72.94
Corr. classified	84.99	78.85	83.51	59.75	72.58
ROC area	62.27	67.80	53.85	67.95	68.17
Out-of-sample disappeared banks ranking by decile of the hazard rate (hold-out sample 2018–2022) (%)					
1–5	31.52	16.06	47.89	18.67	16.61
6	4.55	5.45	7.53	7.23	6.90
7	10.30	9.70	7.83	14.46	9.40
8	9.09	14.24	9.94	15.96	12.85
9	12.42	16.67	13.55	18.07	14.73
10	32.12	37.88	13.25	25.60	39.50

other words the issue of false alarms on the soundness of small banks, which in turn also increases the percentage of banks correctly classified by the models. By including all the selected explanatory variables in Model 5, its overall predictive ability improves, although with a lower Sensitivity rate. If the cut-off is raised to 3 %, as expected, the Sensitivity decreases but the overall predictive capacity of the different models improves, so that false alarms and the supervisory authorities' consequent control work diminish. In comparison with the results of Männasoo and Mayes (2009), Fiordelisi and Mare (2013), Betz et al. (2014), and Mare (2015) the in-sample predictive capacity of our models (at 3 % cut-off) is slightly lower than that reported by the aforementioned authors. For example, their Sensitivity rate is between 70 % and 90 %, as is the percentage of cases correctly classified by their models. However, these authors use very different samples from ours. Therefore, we believe that comparability is limited, given that ours is, as far as we know, a unique study both in terms of the sample used and the models' specifications.

As a further measure of goodness of fit, we report the in-sample ranking of the banks using the estimated probability of exit or the hazard rate. The hazard rate is computed using the estimated coefficients for the variables in the different model specifications. The ranking shows that most of the banks that left the market are in the highest deciles, which is not surprising given the average value of the risk of the small banks that disappeared. Moreover, in Panel B we report two sets of diagnostics for the out-of-sample predictions. In the first instance, we used a training sample that covers the period 2005–2017 while the hold-out sample refers to the years 2018–2022. We believe that this last sample could be valuable for evaluating the predictive capabilities of our models, given that it includes the effects of the 2019 pandemic crisis. We instead opted for a large training sample from 2005 to 2017 which covers multiple episodes of financial crisis to which small European banks were exposed. Further, we employ a training sample consisting of banks located in Austria, Germany, and Italy and a hold-out sample consisting of banks in the remaining countries. This choice is motivated by the relevance and variety that small banks assume in the three countries mentioned, which should provide a valuable assessment of how well the models might do if applied to new data. We rely on the sole 3 % cut-off for the sake of brevity in both out-of-sample predictions and show that the overall predictive power of Model 5 is quite satisfactory except in terms of Sensitivity. Hazard rankings are also presented regarding the in-sample and out-of-sample forecasts in Panel B of Table 4.

A final element to highlight concerns the incremental effect that the *Contagion* variable has on non-surviving banks' probability of exiting the market, compared to estimates in which this variable is not present. Its inclusion helps to better classify healthy banks which remain sound even in the presence of non-surviving banks in the region in which they are located.

3.1.1. Digging into banking size: the role of micro and macro determinants of bank survival

As stated earlier, our analysis focuses on small banks (with less than 5 billion euros in total assets); although the size threshold is very low, there is nevertheless a great deal of variability in terms of operating strategies beneath it. Table 5, for this purpose, provides separate estimates for three sub-samples with intermediate trigger values of 250 million and 1 billion euros.

The first column provides the coefficients associated with the bank-specific and macroeconomic variables for banks with total assets of less than 250 million euros. It emerges that the probability of exit is higher for small, less capitalized, more inefficient banks, that are more exposed to credit risks and show higher loan-to-deposit ratios. This confirms what was stated in the previous comments, where the elements of greater vulnerability related to the period under analysis were provided. The macroeconomic environment also plays a significant role: the probability of the occurrence of the dependent variable "*Event*" increases as the population with advanced educational degrees shrinks, as the population ages, and as monetary policy is looser. The coefficient associated with the variable *Contagion* is positive and strongly significant.

Columns 2 and 3 of Table 5, which are devoted respectively to estimates for the sub-sample of banks with total assets between 250 million and 1 billion euros, and banks with total assets between 1 and 5 billion euros, show coefficients that are only partially in line with those described previously. As regards the microeconomic explanatory factors of exit, the coefficient associated with the size of the bank loses statistical significance for the sub-sample of bigger banks. Therefore, the variable *Size* emerges as a significant factor in explaining

Table 9

Estimates by sub-periods. This table shows in Panel A the complementary log–log model estimations obtained for the two sub-periods 2005–2012 and 2013–2022 by regressing bank exit on the micro and macroeconomic lagged variables as described in Table 1. Reported coefficients are not exponentiated. All microeconomic variables are winsorized at the 1% of each tail. Temporal dummy variables are also included in the model. Robust standard errors clustered on the unit of analysis are reported in parentheses. The superscripts ****, ***, **, and * denote coefficients statistically different from zero at the 0.1%, 1%, 5%, and 10% levels, respectively, in two-tailed tests. This table also displays in Panel B models' goodness of fit concerning the relationship between model predictions and actual events of bank exit. In-sample predictions are computed on the whole sample used to fit the models using a cut-off point equal to 1%, 2%, and 3%. Panel B also reports the ranking of disappeared banks using the estimated hazard rate, from the least to the most risky. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications for the banks in-sample over the two sub-periods. Following Hosmer and Lemeshow (2000) we do not report any R-squared measure (such as the Nagelkerke's pseudo-R-squared) since the authors indicate that a true measure of fit is the one based strictly on a comparison of observed to predicted values from the fitted model.

Panel A	From 2005 to 2012	From 2013 to 2022
L.Size	−0.226****	−0.317****
	(0.064)	(0.033)
L.Capital	−0.072***	−0.055****
	(0.026)	(0.011)
L.Funding gap	0.015	0.049*
	(0.039)	(0.027)
L.Credit risk	0.474****	0.415****
	(0.123)	(0.057)
L.RAROA	0.002	−0.010*
	(0.011)	(0.006)
L.Cost to income	0.023****	0.020****
	(0.005)	(0.002)
L.Income div	0.002	0.006**
	(0.006)	(0.002)
L.Monetary policy	−0.553	−0.127
	(0.360)	(0.176)
L.Concentration	0.083****	0.013
	(0.018)	(0.010)
L.Unemployment	0.032*	0.000
	(0.017)	(0.010)
L.Tertiary education	−0.006	−0.005
	(0.013)	(0.007)
L.Elderly population	0.116***	0.053***
	(0.042)	(0.019)
L.Population density	−0.031	0.104*
	(0.142)	(0.062)
Contagion	1.722****	1.625****
	(0.153)	(0.083)
Year dummies	Yes	Yes
No. of disappeared banks	223	881
No. of banks	2,556	3,501
Mean hazard of disappeared banks	0.057	0.102
Mean hazard	0.020	0.039
No. of obs.	11,411	23,622

Panel B	From 2005 to 2012	From 2013 to 2022
In-sample predictions 1 % cut-off (%)		
Sensitivity	85.65	92.87
Specificity	49.69	27.57
Corr. classified	50.39	30.10
ROC area	67.67	60.22
In-sample predictions 2 % cut-off (%)		
Sensitivity	62.78	85.01
Specificity	76.60	52.62
Corr. classified	76.33	53.88
ROC area	69.69	68.81
In-sample predictions 3 % cut-off (%)		
Sensitivity	57.40	79.69
Specificity	82.17	61.95
Corr. classified	81.68	62.63
ROC area	69.78	70.82
In-sample disappeared banks ranking by decile of the hazard rate (%)		
1–5	14.80	14.51
6	8.07	5.44
7	8.52	7.86
8	9.87	11.97

(*continued on next page*)

Table 9 (*continued*)

Panel B	From 2005 to 2012	From 2013 to 2022
9	16.14	16.32
10	42.60	43.89

exit for smaller banks: dwarf banks, unable to exploit the beneficial effect that stems from economies of scale, are most exposed to the risk of disappearance. The level of *Capital* maintains its statistical significance only for banks with total assets below the threshold of 1 billion euros; the same occurs for *Credit risk*, while efficiency remains a significant covariate in all the estimations. Conversely, the *Funding gap* and risk-adjusted profitability gain statistical significance for the larger banks sub-sample. Overall, these outcomes can be explained if one considers that these two sub-samples of larger (but still small) banks have easier and more frequent access to financial markets for funding; this leads to a different set of signaling indicators that can explain the dynamics in their disappearance.

As regards macroeconomic covariates, we observe a scattered pattern of statistically significant coefficients. Only *Monetary policy* and *Contagion* show constant behavior, being associated with strongly significant coefficients. The latter covariate deserves a further note: the magnitude of the coefficients shown in Table 5 increases for smaller size sub-samples, indicating that the disappearance of banks in a specific area generates spillovers that exert a higher pressure on smaller banks.

The goodness of fit analyses contained in Panel B of Table 5 show how the overall predictive quality of the model soars as the size threshold of the sub-sample of analyzed banks increases. This highlights how the disappearance of extremely small banks is a poorly predictable event, which indirectly justifies the pressure from regulators and supervisors for M&A phenomena to increase the size threshold of smaller banks. The out-of-sample goodness of fit is generally in line with that reported in Table 4.

3.1.2. *Do the business models of small banks all perform equally?*

The sample analyzed is made up of many commercial, savings, and cooperative banks; these three categories reflect differences between business models, from which it is reasonable to hypothesize that different competitive behaviors (and therefore different levels of financial vulnerability) may arise. Fiordelisi and Molyneux (2006) state that commercial banks are entities that are predominantly oriented towards creating value for their shareholders (shareholder value-oriented banks); savings, and to an even greater extent cooperative banks, do not focus on maximizing profits, but pursue objectives of the welfare of different stakeholders at a local level (stakeholder value-oriented banks). Among the latter, there are certainly the bank's shareholders (often not surprisingly defined as "members"), but also associations and other local structures often linked to the non-profit sector (Fiordelisi et al. 2022). These characteristics make cooperative banks more inclined to prioritize relationship banking policies, reducing agency costs (Rasmusen 1988), and maintaining a low level of risk and a high level of capitalization. Their small size, however, leads to higher levels of income concentration and makes them less able to attract high-profile managerial figures (Fiordelisi et al. 2022). It is, therefore, reasonable to expect that the type of business model leads to differences in the financial results of the analyzed banks; however, given the advantages and disadvantages linked to the choice of a shareholder value- or stakeholder value-oriented model, the final result in terms of disappearance rates must be empirically determined.

Table 6 shows estimates for sub-samples of banks that are homogeneous from a business model perspective. The average risk of commercial banks and disappeared banks that fall into this sub-sample is the highest among the different business models.

Commercial banks (first column) show significant coefficients associated with three bank-specific variables, namely *Credit risk*, *RAROA* and *Cost to income*. Among the macroeconomic variables, market concentration, unemployment, and the dummy signaling the presence of multiple non-surviving banks show significant coefficients.

As regards cooperative and savings banks, the outcome of the analysis provides a consistent picture for the two sub-samples. In particular, the survival of banks appears to be facilitated by greater size, higher levels of capitalization, lower credit risk, and greater efficiency. The proxy for income diversification is associated with a statistically significant coefficient only for the cooperative banks sub-sample. Among the macroeconomic variables, statistically significant coefficients are found for *Elderly population* and *Population density*, while *Monetary policy* is associated with a statistically significant coefficient only for cooperative banks. However, in all estimates reported in Table 6, the *Contagion* variable exhibits a very high statistical significance.

Overall, the predictive ability of the model appears higher for savings banks but at the cost of a lower Sensitivity rate.

3.1.3. *Financial versus strategic exits: micro and macro determinants at work*

The concepts of survival or market exit can be easily represented through binary variables from Stigler's (1958) perspective. However, Chiorazzo et al. (2018) recall that this approach, while extremely simple to apply in empirical research, neglects the fact that the disappearance of an operator from the market can occur either for financial reasons (for example episodes of failure) or for strategic reasons (for example through M&A operations carried out with other banks, not with the aim of rescue, but for strategic purposes, including preventing future situations of distress). This insight has practical implications which are not negligible: considering financial and strategic exit as identical events paradoxically leads to the risk of confusing entities that have exited the market due to serious financial distress and entities that have become the object of other companies' interest due to their virtues (including in terms of profitability).

As stated previously, to separate financial and strategic exits we rely on the annual Z-score of the banks; more precisely, banks that show a Z-score in the lower quartile of the distribution of this variable are associated with financial exit, while the other banks are associated with strategic exit. 31.6 % of the banks included in our sample occupy the lower quartile of the Z-score; among them, 76.5 % have been associated with a financial exit. Conversely, 25.7 % of the banks included in the sample are found in the top quartile; among these, 18.6 % are associated with financial exit.

Following this approach, Table 7 provides separate estimates for sub-samples attributable to financial and strategic exit.

The first column, devoted to financial exits, shows that the probability of this outcome rises for banks that are less capitalized, less efficient, less profitable, more exposed to non-interest incomes, and that have a higher funding gap and credit risk. Among the macroeconomic covariates, higher market concentration (Chiorazzo et al. 2018), population age, and density increase the probability of a financial exit. Again, the coefficient associated with the variable *Contagion* is strongly significant.

The second column, related to strategic exits, shows some peculiarities; in this specification, *Size* is associated with a negative and significant coefficient while we observe a positive coefficient being associated with *RAROA*. The latter result seems to imply that small banks with increasing risk-adjusted profitability are more attractive for strategic exits, such as mergers or acquisitions. Moreover, the proxies for funding gap and income diversification do not show a significant impact on this kind of market exit. Among the macroeconomic covariates, only *Elderly population* and *Contagion* are associated with (strongly) significant coefficients.

Diagnostics of the predictive power in-sample provide slightly better results for cases of financial exit.

3.2. Robustness checks

Within the area under examination, some countries (namely, Austria, Germany, and Italy) are characterized by a high number (and significant market share) of small banks: the estimation models described above were therefore applied to a sub-sample of banks belonging to these three countries to test whether the results of the econometric analysis remain unchanged and are not driven by other countries. Table 8 provides the outcome of this additional test.

Overall, the coefficients associated with the different explanatory variables retain their sign when compared with those in Table 4; there are, however, slight variations in the statistical significance found. Among the bank-specific variables, the explanatory contribution of the *Funding gap* is lost in all the specifications; the same occurs with the coefficient associated with *Population density* among the macroeconomic variables.

As reported in Panel B of Table 8, the results of the tests relating to the predictive ability of our in-sample models do not change significantly compared to what was found for the entire sample. Out-of-sample predictions are not reported given that the sample of banks in Austria, Germany, and Italy is used as a training sample to evaluate its predictive capacity on the hold-out sample represented by the remaining European countries (see Table 4).

In a further test, we consider the sub-sample of banks excluding Germany; the main results proved unchanged, especially for microeconomic determinants and the variable *Contagion*. These outcomes are available on request.

Our work covers a particularly lengthy period, during which the economic and financial conditions in which banks operate have changed significantly. In this regard, the topic of the level of interest rates (and more generally of looser monetary policy) is particularly evocative. In fact, in 2012, Mario Draghi's famous speech (remembered for the renowned quote "Whatever it takes") gave birth to a more active approach by the European Central Bank, leaving room for non-conventional monetary policies; moreover, since 2014 many countries have experienced particularly low or even negative interest rates policy (NIRP). This has resulted in a widespread contraction of interest income margins for the banking sector (Borio and Gambacorta 2017; Claessens et al. 2018; Committee on the Global Financial System 2018). In some cases, however, the ability to diversify revenue sources has allowed banks to offset losses in interest income with non-interest income flows (Altavilla et al. 2018; Lopez et al. 2020). Considering the limited ability of small banks to diversify their revenue sources, as they focus mainly on deposit-taking and lending, it is conceivable that the pattern of bank exits was different before and during the implementation of non-conventional monetary policies. Hence, Table 9 divides the time span under scrutiny into two sub-periods: the first between 2005 and 2012 and the second from 2013 to 2022.

Overall, the microeconomic covariates are associated with coefficients having the same sign as those shown in Table 4 (Model 5), although the significance sometimes differs. The banks that exited the market during both sub-periods were smaller, less capitalized, less efficient, and more exposed to credit risks. The proxy for income diversification is associated with a significant and positive coefficient in the period 2013–2022; this could indicate that during a period of squeezing margins small banks tried to diversify their revenues, but the overall outcome was a higher probability of exiting the market. In this same sub-period, banks with lower profitability and higher funding gaps have been associated with higher exit rates.

Among the macroeconomic variables, it is shown that *Elderly population* and *Contagio*n play a significant role in both the sub-periods. *Concentration* is associated with a positive and significant coefficient only during the period 2005–2012, suggesting that in those years more concentrated markets increased the probability of experiencing a strategic or financial exit. A weak and positive significant coefficient associated with *Unemployment* is also found during the first sub-period; the same occurs for *Population density* for the years 2013–2022. The mean hazards for this latter period are much higher than those recorded in the previous period.

Diagnostics to ascertain the predictive power of the models provide better in-sample results for the 2005–2012 period, when – despite the outbreak of the international financial crisis – the macroeconomic and financial environment nevertheless presented more typical conditions than in the following decade.

4. Policy implications

Small banks play a fundamental role in European countries; the exit of these intermediaries therefore represents a phenomenon that must be managed carefully. The focus placed by regulatory and supervisory bodies on significant entities has often led to an underestimation of the effects that can derive from the disappearance of small banks. These latter events can have systemic outcomes that are far greater than expected, with negative repercussions for the areas in which small banks operate and for the financial system as a whole. This opinion is shared by the European Commission's recent Impact Assessment Report (European Commission 2023), according to which the distress of even small banks may lead to the destruction of economic value locally/regionally or the disruption of depositors' confidence, especially for small geographical areas. For these reasons, it is extremely important to have predictive tools that allow us to appreciate the exposure of small banks to idiosyncratic risks and/or those that are attributable to the local/regional economic context of these banks.

The predictive capacity of the models run in this paper to identify small banks' exits highlights very low levels of Type 1 errors, while Type 2 errors are much more frequent: this means that selected variables can intercept almost all the cases that have proved to be truly problematic but also generate many false signals concerning banks that can recover from temporary difficulties. Although from the point of view of supervisory authorities, the minimization of Type 1 errors is of greater importance than Type 2 ones, nevertheless our evidence indicates how complex it is to develop models that optimize both error levels, at least where small banks are concerned. This increased workload to which the authorities are exposed can also explain why bank supervisors push toward a process of aggregation, including through the formation of highly integrated groups among small banks. In this case, however, the parent company should act not as a mere manager of geographically diversified assets (small local banks), but should rather act for crisis prevention or resolution purposes, considering the macroeconomic effects that may arise at a territorial level, as also noted by the above-mentioned European Commission's report.

As demonstrated by our main findings, the possible occurrence of situations in which local banks disappear confirms the importance of the role of the capital cushion held and the level of operational efficiency on which small banks can rely. This is an important outcome both for its managerial implications (a competitor's crisis tends to undermine a bank's soundness regardless of its financials) and for its supervisory ones (mapping information at the territorial level takes on greater significance in predicting disappearance than information related only to analyzing bank balance sheets).

From a regulatory point of view, our results confirm that the basic approach of the Basel III framework, focused on strengthening bank capital, is correct. The existence of higher levels of capitalization reduces the probability of exit from the market of the banks in our sample, both for financial and for more strategically related reasons. However, the risk-based capital requirements related to the new calculation of Risk Weighted Assets (RWA) for credit and market risks envisaged by the finalization of Basel III require further organizational and management efforts, in terms of risk management, compliance and, once again, more capital. This could significantly increase regulatory costs (Gržeta et al. 2023), with a negative impact on the level of banks' cost to income ratio: in light of our empirical results, this effect raises potential concerns regarding the survival of small banks.

The finalization of Basel III seems to make it complex for small banks to choose stand-alone solutions. Appropriate aggregation phenomena, often hoped for by the authorities (e.g. Enria 2023; Fernandez-Bollo et al. 2021), especially where pockets of inefficiency tend to be created through phenomena of overbanking capacities (Gardò and Klaus 2019), can be functional in achieving economies of scale linked to costs of compliance as well as gaining easier access to capital markets. Recent studies, although limited to national experiences (in this specific case, Italy) show how aggregation into integrated groups (Cornée et al. 2018) can allow small banks to recover in terms of efficiency (Beccalli et al. 2023), gain protection regarding the stability of the banks themselves (Single Resolution Board 2023), while safeguarding the traditional biodiversity of the banking system.

5. Conclusions

Based on a wide sample of banks headquartered in 27 European countries over the period 2005–2022, this paper tests the influence that microeconomic and macroeconomic variables have on small banks' probability of exit from the market, evaluating the predictive power of the explanatory models employed.

One of the first contributions of our study relates to the fact that microeconomic and macroeconomic factors have a similar signaling value in identifying potential exits for small banks; in a certain sense, the territorial link seems to blur the boundaries of a bank, leading it to absorb the virtues and critical issues of the territory in which it is located. Models incorporating microeconomic and macroeconomic covariates are good descriptors of the pattern of events observed in our database: this means that both the micro and the macroeconomic data are predictive of the exit of small banks.

A further contribution of our work concerns the importance of the soundness of peer banks in local areas, which appears to be crucial to the survival of small banks. We show that the occurrence of contagion episodes exposes small banks to a higher risk of exit and has a significant predictive value that also minimizes exposure to Type 2 errors. The relationship of trust that exists with customers and the apparent greater fragility that the public could associate with dwarf banks exposes them to critical factors that are at least partially exogenous to corporate strategies. Since our work typically has a local focus, the contagion effects deriving from the concomitant crisis of national champions (or small banks in nearby regions) have not been considered here: this constitutes a further stimulus for digging deeper into the channels of contagion transmission.

Our work also highlights that the role played by the direction of monetary policy is not always significant across all different specifications and sub-samples. This finding is, for instance, not in line with the recent scientific debate and empirical evidence in this regard, which have ascribed the greater fragility to which small banks are exposed to prolonged periods of low or even negative rates.

This study opens the door to subsequent research on the effect that belonging to a differently integrated network or group can have on the survival of small banks. The researches available so far are territorially limited (usually to a single country) and focused on specific explained variables such as cost economies or profitability.

Additionally, the available empirical studies (including our work) do not account for the potential crowding out effect – or the beneficial impact on cost efficiency – played by technology on small independent banks, due to the inconsistent availability of reliable data on this topic at a local level. Finally, given the specific features of the sample employed for this study – i.e. a unique dataset of multi-country small banks– our results cannot be fully compared with those of existing literature.

CRediT authorship contribution statement

Federica Poli: Writing – original draft, Supervision, Methodology, Data curation. **Simone Rossi:** Writing – original draft, Methodology, Data curation, Writing – review & editing. **Mariarosa Borroni:** Writing – original draft, Supervision, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors thank Jonathan A. Batten (the editor), as well as two anonymous reviewers for their constructive and insightful comments. We are also grateful for the helpful suggestions received from participants at the Conference "The Future of Financial Mutuals" at Università Cattolica del Sacro Cuore (December 1st., 2023, Milan).

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